Mechanical Manufacturing Design And Computer Simulation Optimization In Intelligent Manufacturing

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Intelligent Manufacturing, based on computer simulation optimization, promotes the mechanical manufacturing design greatly. The technology allows to test and optimize mechanical products virtually, and deliver more effective and economical manufacturing processes and advanced software applications with complex algorithms the design is faster, requires less physical prototyping, and is more accurate. In addition, simulation based on optimization can assess a number of design alternatives or operating scenarios to find the best solutions. This method improves the intelligence level of manufacturing systems, enables the mass customization and the rapid innovation of mechanical products. In an intelligent manufacturing environment, Computer Simulation Optimization synthesizes the features of design efficiency, cost reduction and effective utilization of resources and contributes to elevating design efficiency of manufactures and curbing down design cost, ultimately leading to high productivity and high-quality design.

Keywords: Accurate; Dramatically; Mechanical; Optimization; Efficiency

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1. Introduction

In today's industry, the demand for high-quality, cost-effective, and customizable products is on the rise, and the competition in the market is becoming more and fiercer [1]. To stay ahead in this competitive environment, companies are turning to Intelligent Manufacturing, which combines advanced technologies such as mechanical manufacturing design and Computer Simulation Optimization. This approach offers numerous benefits, including increased efficiency, reduced costs, and improved product quality. In this essay, we will discuss the role of mechanical manufacturing design and Computer Simulation Optimization in Intelligent Manufacturing and its impact on the industry [2]. Mechanical manufacturing design creates and develops mechanical components and products using computer-aided design (CAD) software. It involves using mathematical models, simulations, and virtual prototypes to design and test various product components, such as parts, assemblies, and systems. This allows manufacturers to visualize their products and make necessary adjustments before moving to the production phase. Sophisticated surveillance devices in precision and ultra-precision machining enable a better process control and product quality, thus favoring the realization of efficient and effective mechanical production in intelligent manufacturing systems [3]. Furthermore, mechanical manufacturing design is a crucial element in the development of Intelligent Manufacturing as it enables the integration of various technologies such as 3D printing, automation, and robotics. Mechanical production is combined with 3D printing for rapid and low-cost customization with less dependence on conventional processes [4]. Computer-aided design (CAD) simulations and automation enhance efficiency, identify design defects at an early stage, and avoid defects in actual production [5]. Cyber-physical manufacturing systems based on digital twin integrate the IoT, artificial intelligence (AI) and simulation technologies to optimize the production process, decision making, and the efficiency of intelligent manufacturing system; [6]. In this approach, different teams, such as design, production, and quality control, work together on a single digital platform to design and develop a product in real-time. The intelligent manufacturing virtual simulation teaching platform allows the design and operation of mechanical products to be implemented and tested in a digital space, and can enhance the precision of the design, the optimization of process, and the efficiency of the production [7]. Computer Simulation Optimization has been proven to enhance productivity and lower cost via virtual modeling [8]. It maximizes production system and its throughput [9]. Furthermore, it enhances supply chain performance and facilitates high quality and low-cost manufacturing [10]. Learning-based simulation optimization enhances the accuracy of decisions and competitiveness [11], and the time and cost of design are reduced and throughput, efficiency and product reliability are increased. The design and simulation optimization of the mechanical manufacturing can enhance the product design, decrease the cost by detecting the defects in the early stage, improve the production efficiency through the optimization of the processes and realize the predictive maintenance by monitoring the equipment and predicting the repairs. The contributions of the proposed CSDCOIM model are as it, recognize the deficiencies for current integrated optimization methods, establish unified CSDCOIM design, simulation, optimization, promote early data-driven decision-making, seek for potential improvement and high quality as well as low cost under real-time constraints and performance could, and adapt to complex intelligent manufacturing. In this paper, a simulation-based integrated design methodology is developed in the field of Intelligent Manufacturing for the betterment of efficiency, cost, and quality, which is assessed by recall, accuracy, specificity, and miss rate.

2. Materials and method

Abstract: Some important links in the modern manufacturing industry are mechanical manufacturing design and Computer Simulation Optimization [12]. They are programs that use engineering methodologies and advanced tools to develop mechanical components and machines, providing efficient production. Mechanical production in the intelligent system is based on design, simulation and optimization. CAD builds up models, CAE verifies the performance, and optimization adjusts the parameters based on data. The means of these linked subsystems promote cost, quality and efficiency and allow for continuous feedback-based process improvement in manufacturing. While they are significant, Intelligent Manufacturing has numerous issues and problems. Mechanical manufactured design and Computer Simulation Optimization problems are based on the lack of highly skilled personnel, which is one of the core issues. Shortage of skills still acts as a barrier to manufacturers with 40–50% of companies being deficient in CAD/CAM knowledge, leading to bottlenecks, and just 20–25% of the labor pool having the necessary skills to run simulations. Mechanical product design and simulation optimization is based on the technical expertise of CAD/CAM/CAE, and scarce technical professional are demanded [13]. The high costs of purchase and maintenance of tools hamper the adoption, notably by SMEs [14]. Implementation is obstructed by complexity of system and steep learning curve [15]. Incompatibility between software and hardware hinders integration, resulting in inefficiency and lag [16]. Accuracy of simulation is also an issue since models may have certain deviations from field conditions, which may cause risk especially in critical industries [17]. These challenges have limited propagation in smart manufacturing [18]. Meeting those requirements involves training as well as technology and integration investment. Intelligent manufacturing which incorporates AI, machine learning, and IoT to improve manufacturing processes [19]. They enable improved design and optimization capabilities [20]. They have the potential to improve accuracy, allow early detection of problems and higher efficiency, thus better final product quality and shorter lead times [21].

2.1. Proposed Model

This model is developed to conduct design and optimization work on mechanical manufacturing processes with Computer Simulation Optimization technology in Intelligent Manufacturing, which has both theoretical research significance and practical use value.

$$\mathrm{Y_{s+1}} = \mathrm{d}\left(\mathrm{y_s}, \mathrm{w_s}\right) \tag{1}$$

The iterative design update is expressed as $Y_{s+1} = d\left(Y_s, W_s\right)$, where Y_s represents the current design state at iteration s, Y_{s+1} denotes the updated design state, W_s is the set of design variables and manufacturing process parameters, and $d(\cdot)$ is the design update function based on simulation and optimization results. This equation describes the progressive refinement of the design, where each iteration improves performance while satisfying manufacturing constraints.

$$X_{s+1} = \sum_{j=1}^{m_a} a_j X_{s+1-j} + \sum_{j=1}^{m_b} c_j W_{s+1-j} \tag{2}$$

The design variable update is expressed as $X_{s+1} = \sum_{j=1}^{m_a} a_j X_{s+1-j} + \sum_{j=1}^{m_b} c_j W_{s+1-j}$, where X_{S+1} is the updated design variable, X_{S+1-j} and W_{s+1-j} represent previous design states and process parameters, and a_j, c_j, m_a, and m_b are weighting coefficients and iteration limits. This equation captures the influence of past design process conditions to refine the current design.

$$P_{\text{melt}} = E_{\text{melt}} \times \frac{z_{\text{shot}}}{T} \tag{3}$$

The melting process parameter is expressed as $P_{\text{melt}} = \frac{E_{\text{melt}} \times Z_{\text{shot}}}{T}$, where P_{melt} represents the melting power, E_{melt} is the energy required for melting, Z_{shot} denotes the shot size or material quantity, and T is the processing time and it defines the relationship between energy input and material processing rate. The first is getting data and information about the product design requirements and manufacturing constraints. In this study, the dataset is composed of multiple design and manufacturing parameters that affect the process of optimization. CAD considers material, geometry, process constraints; simulation is used for parameter optimization.

$$\begin{aligned} QE(j,q) &= \sum_{i=1}^{E_f} QU(i,j,k,l) \\ &+ \sum_{i=1}^{E_f-1} QQ\left(i,l,(j,k_1),(j+1,k_2)\right) \end{aligned} \tag{4}$$

The quality evaluation is expressed as $QE(j,q) = \sum_{i=1}^{E_f} QU(i,j,k,l) + \sum_{i=1}^{E_f-1} QQ\left(i,l,(j,k_1),(j+1,k_2)\right)$, where $QE(j,q)$ represents the overall quality metric, QU and QQ denote unit and transitional quality measures, and $E_f, i, j, k, l, k_1, k_2$ are indices and parameters of the process, capturing cumulative and sequential effects to support optimizationunder manufacturing constraints. Equation (4) results from summing quality contributions of both the unit-level and sequential processes.

$$\max d(j,q) = \frac{1}{QE(j,q)} \tag{5}$$

The objective function is expressed as $\max d(j,q) = \frac{1}{QE(j,q)}$, where $d(j,q)$ represents the optimization objective and $QE(j,q)$ is the quality evaluation metric, indicating that maximizing performance is achieved by minimizing quality-related deviations.

$$\min B_q = \sum_{j=1}^{n} q_j \tag{6}$$

The objective function is expressed as $\min B_q = \sum_{j=1}^{n} q_j$, where B_q represents the total cost or burden metric and q_j denotes individual quality or cost components over n elements, aiming to minimize the overall system cost while satisfying design and manufacturing constraints. The form of cost function in Eq. (6) results from the minimization of the summation of cost terms, which is an industrially practical scenario. Optimized designs reduce lead time and errors, allowing for efficient production and quality improvement, cost saving and rapid manufacturing of complex products on data-based process. CSDCOIM coordinates the design, simulation and optimization processes with feedback for an adaptive, efficient, cost-effective, robust intelligent manufacturing, and shows superior performance over that of G-JUST, MMDSIM and CIS-DS.

2.2. Construction

The intelligent manufacturing system combines CAD and simulation optimization to the design of high-efficiency system, and it is realized by engineering application from the system level to the process level in the view of the system with specific constraints, as shown in Fig. 1.

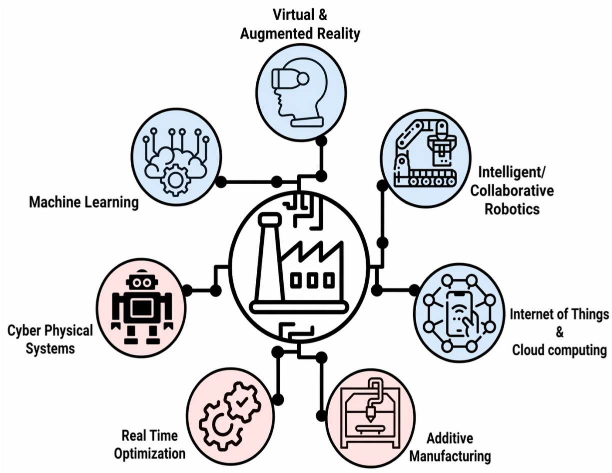

Fig. 1. Construction diagram supporting performance evaluation in Intelligent Manufacturing using Computer Simulation Optimization.

As showed in Fig. 1, the IMS architecture combines CPS, IoT, cloud computing, real-time optimization and additive manufacturing, allowing for data exchange, real-time communication, performance enhancement, and flexible production. The data gathering constructs a virtual model of the factory which allows simulation to detect bottlenecks and optimize factory processes. Collaborative design allows for sharing of data in real time and for working in parallel, resulting in efficiency. The IoT and the CPS enable real-time monitoring and updating virtual models to predict bottlenecks and optimize control decisions in a dynamic and accurate manner in the manufacturing. This will also involve directly adding intelligent functions into the virtual factory to monitor and optimize manufacturing in real-time.

2.3. Operating principles

The system runs in stages concept generation, CAD design, simulation, optimization, and deployment, and continuous real-time feedback leads to better system performance and a clear understanding of manufacturing operations and the way they evolve. The design of mechanical products is to produce cost effective, reliable and high-quality products with the help of engineering software's and also has a great emphasis on detailed design and concept generation to fulfill the product requirements.

$$\mathrm{q_j} = \mathrm{q_{out}^{Em}} + \mathrm{q_{rf}} - \mathrm{Q_{push}} \tag{7}$$

The parameter is defined as $q_j = q_{\text{out}}^{E_m} + q_{rf} - Q_{\text{push}}$, where q_j represents the net quality or performance metric, $q_{\text{out}}^{E_m}$ denotes the output influenced by energy or efficiency factor E_m, q_{rf} is the reinforcement or residual factor, and Q_{push} represents process loss or opposing force, capturing the balance of contributing factors.

$$\eta_{\mathrm{ji}} = \frac{1}{\mathrm{f_{ji}}} \tag{8}$$

The efficiency relationship is expressed as $\eta_{ji} = \frac{1}{f_{ji}}$, where η_{ji} represents the efficiency between components j and i, and f_{ji} denotes the associated loss or resistance factor, indicating that efficiency improves as losses decrease. The design process proceeds with computer-aided design (CAD) software to create 2D and 3d models. The application of CAD in the design process has the direct consequence of making the decision process more efficient, since it is now possible to quickly assess several design options. The models under development are experimented with simulations to assess their performance and help to find possible problems in an early stage, and optimization methods. Simulation optimizes the parameters with constraints and can be extended to predictive maintenance (using sensors and intelligent fault prediction).

$$\tau_{\mathrm{ji}}(\mathrm{q}+1) = (1-\rho)\tau_{\mathrm{ji}}(\mathrm{q}) + \Delta\tau_{\mathrm{ji}} \tag{9}$$

The update rule is expressed as $\tau_{ji}(q+1) = (1-\rho)\tau_{ji}(q) + \Delta\tau_{ji}$, where τ_{ji} represents the parameter (e.g. pheromone/intensity) between components j and i, ρ is the decay factor, and $\Delta\tau_{ji}$ is the update increment, modeling adaptive optimization under manufacturing constraints.

$$\Delta\tau_{\mathrm{ji}} = \sum_{\mathrm{s}=1}^{\mathrm{m}} \Delta\tau_{\mathrm{ji}}^{\mathrm{s}} \tag{10}$$

The increment is defined as $\Delta\tau_{ji} = \sum_{s=1}^{m} \Delta\tau_{ji}^{s}$, where $\Delta\tau_{ji}^{s}$ represents individual contributions from m sources or solutions, capturing cumulative effects to enhance optimization performance in the design and manufacturing process. Virtual experiments allow the design variables to be tested to find optimal solutions before production. Smart manufacturing combines AI, IoT and data analytics along with real-time feedback. Real-time data, predictive maintenance and dynamic configuration is being enabled by IoT and AI technologies, while iterative co-design /co-simulation/co-manufacturing lead to improved decisions, less downtime and better system efficiency.

2.4. Functional working

Mechanical manufacturing design is the combined product, component and material selection and process planning for performance, functionality, and cost optimization, as depicted in Fig. 2 Functional Working Diagram.

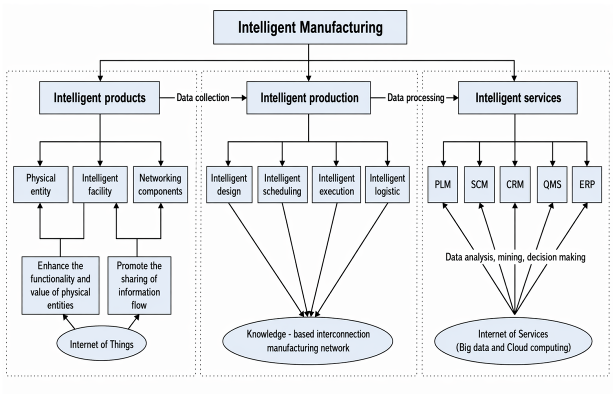

Fig. 2. Functional working diagram illustrating Intelligent Manufacturing process integration and data flow.

As illustrated in Fig. 2, the intelligent manufacturing system unifies intelligent products, production, and services and applies IoT for communication, KMN for manufacturing and IoS based on big data and cloud computing for decision-making. Simulation-based optimization evaluates materials, machines, and processes.

3. Results and discussion

The result is that simulation can enhance the design efficiency, quality, cost and time mainly by easily detecting design faults. The simulated CSDCOIM model for the proposed approach is compared with G-JUST, MMDSIM, and CIS-DS for evaluating its performance. Statistical validation provides for the reliability of the results through multiple runs of the simulation, and mean recall, accuracy, standard deviation, and 95% confidence intervals are reported to show the consistency and stability of the model.

3.1. Recall

Simulation-based design enables materials, structure and assembly of the design to be optimized for efficient performance. It improves quality, saves time and cost, and detects faults at a very early stage, in which they can be corrected to achieve better proto- type performance. In Table 1, the comparison of recall for the existing and proposed models is the average value with standard deviations and 95% confidence intervals, to show the reliability and stability of results. Fig. 3 shows the Comparison of Recall. Increasing recall indicates the model effectively identifies relevant manufacturing specifications even as input size grows.

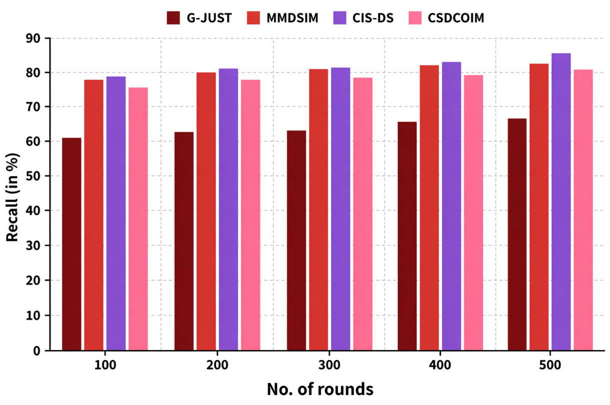

Fig. 3. Comparison of recall performance metric among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

3.2. Accuracy

The mechanical manufacturing is about necessity, which can be attained by CAD/CAM/CAE tools that support designing, simulating, and optimizing, as well as be augmented by intelligence to develop products with accuracy and high quality. The accuracy comparison of existing and proposed models is depicted in Table 2 in which mean values, standard deviation and 95% confidence interval are also provided to show stability and reliability of the results. Fig. 4 shows the Comparison of Accuracy. Increasing accuracy validates reliable optimization decisions.

These results show that CSDCOIM can achieve a good accuracy and recall rate for multi-label classification, similar to CIS-DS, which balances precision and sensitivity, leading to a decrease in false positives and stable and robust optimization results.

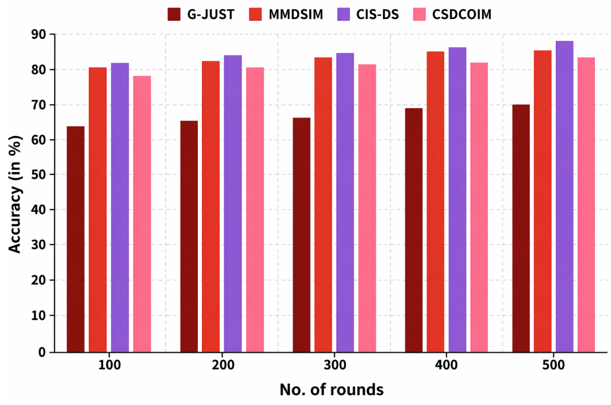

Fig. 4. Comparison of accuracy as a key performance metric among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

3.3. Specificity

The efficient and economical design of mechanical products and their manufacturing processes is widely applicable in such fields as materials and processing. Simulation models are used to assess scenarios of best practices, as presented in Table 3 and Fig. 5. Higher specificity means that the model effectively prunes the inferior solutions, which increases the precision of the decisions. This leads to an improved quality of the solution and less waste of computations.

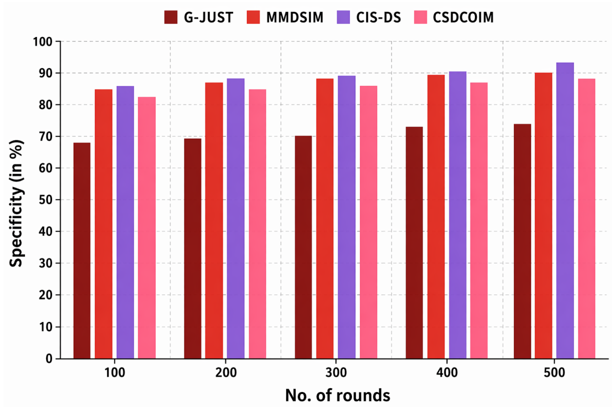

Fig. 5. Comparison of specificity as a key performance metric among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

3.4. Miss Rate

In mechanical manufacturing design and Computer Simulation Optimization in Intelligent Manufacturing, the miss rate reflects failing to hit targets as a result of design imperfections or simulations that are not accurate; enhancing model fidelity and validation, as well as quality of the data,

Table 1. Comparison of Recall (Mean ± SD with 95% Confidence Interval) among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

No. of Inputs	G-JUST	MMDSIM	CIS-DS	CSDCOIM
100	61.02 ± 1.10 (58.90-63.14)	77.87 ± 1.25 (75.42-80.32)	78.68 ± 1.30 (76.14-81.22)	75.72 ± 1.20 (73.38-78.06)
200	62.51 ± 1.15 (60.26-64.76)	79.84 ± 1.30 (77.29-82.39)	81.10 ± 1.35 (78.45-83.75)	77.92 ± 1.25 (75.47-80.37)
300	63.31 ± 1.20 (60.96-65.66)	80.97 ± 1.35 (78.32-83.62)	81.51 ± 1.40 (78.77-84.25)	78.72 ± 1.30 (76.17-81.27)
400	65.64 ± 1.25 (63.19-68.09)	82.16 ± 1.40 (79.42-84.90)	83.11 ± 1.45 (80.27-85.95)	79.39 ± 1.35 (76.74-82.04)
500	66.65 ± 1.30 (64.10-69.20)	82.55 ± 1.45 (79.71-85.39)	85.43 ± 1.50 (82.49-88.37)	80.82 ± 1.40 (78.08-83.56)

Table 2. Comparison of Accuracy (Mean ± SD with 95% Confidence Interval) among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

No. of Inputs	G-JUST	MMDSIM	CIS-DS	CSDCOIM
100	64.02 ± 1.10 (61.90-66.14)	80.87 ± 1.25 (78.42-83.32)	81.68 ± 1.30 (79.14-84.22)	78.72 ± 1.20 (76.38-81.06)
200	65.51 ± 1.15 (63.26-67.76)	82.84 ± 1.30 (80.29-85.39)	84.10 ± 1.35 (81.45-86.75)	80.92 ± 1.25 (78.47-83.37)
300	66.31 ± 1.20 (63.96-68.66)	83.97 ± 1.35 (81.32-86.62)	84.51 ± 1.40 (81.77-87.25)	81.72 ± 1.30 (79.17-84.27)
400	68.64 ± 1.25 (66.19-71.09)	85.16 ± 1.40 (82.42-87.90)	86.11 ± 1.45 (83.27-88.95)	82.39 ± 1.35 (79.74-85.04)
500	69.65 ± 1.30 (67.10-72.20)	85.55 ± 1.45 (82.71-88.39)	88.43 ± 1.50 (85.49-91.37)	83.82 ± 1.40 (81.08-86.56)

Table 3. Comparison of specificity as a performance metric (in %) among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

No. of Inputs	G-JUST	MMDSIM	CIS-DS	CSDCOIM
100	68.02	84.87	85.68	82.72
200	69.51	86.84	88.10	84.92
300	70.31	87.97	88.51	85.72
400	72.64	89.16	90.11	86.39
500	73.65	89.55	92.43	87.82

lead to a decrease in misses. Table 4 shows the comparison of Miss rate between existing and proposed models. Fig. 6 shows the Comparison of Miss rate. The miss rate increases slightly with complexity, demonstrating controlled behavior and providing a dependable detection of critical regions, less loss of optimal solutions, and efficient optimization of large-scale problems.

The results demonstrate that SDC-CIM can improve efficiency, reduce cost, enhance quality, and guarantee scalability, its integrated design, simulation and optimization superiority lies in making better decisions adaptively, feedback-driven, which also has been verified by G-JUST, MMDSIM and CIS-DS. Propagation of errors from variation material and process leads to higher miss rate; calibration bridges simulation and real world, thus makes prediction more reliable. Table 5 shows the comparison on the miss rates (%) of G-JUST, MMDSIM, CIS-DS, and CSDCOIM given different input sizes.

3.5. Impact of CAD/CAM Compatibility and Specificity on Sustainable Manufacturing

Effective production relies on CAD/CAM–simulation compatibility to ensure a smooth data flow. With the increase of specificity, the efficiency of the material utilization is improved, and the waste is reduced; CSDCOIM demonstrates 8-12% higher utilization and ∼10% less waste. The specificity–sustainability trade-offs for all models are given in Table 6.

4. Conclusion

These steps are part of the mechanical manufacturing design, which is making a physical product from concept

Table 4. Comparison of miss rate as a performance metric (in %) among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

No. of Inputs	G-JUST	MMDSIM	CIS-DS	CSDCOIM
100	72.02	87.87	88.68	87.72
200	73.51	89.84	91.10	89.92
300	74.31	90.97	91.51	90.72
400	76.64	92.16	93.11	91.39
500	77.65	92.55	95.43	92.82

Table 5. Impact of Specificity on Sustainability Metrics.

Model	Specificity (%)	Material Efficiency (%)	Waste Reduction (%)
G-JUST	73.65	78.20	6.50
MMDSIM	89.55	85.40	9.20
CIS-DS	92.43	88.10	11.30
CSDCOIM	87.82	86.50	10.00

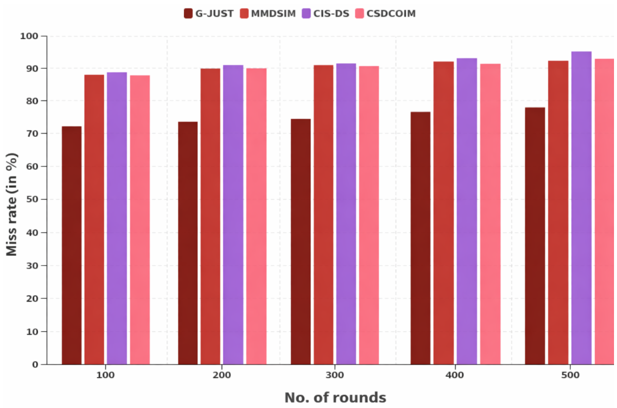

Fig. 6. Comparison of miss rate as a key performance metric among CSDCOIM, G-JUST, MMDSIM, and CIS-DS models.

to reality by applying the principles and techniques in those designing methods to achieve requisite quality standards, leading them into fabrication. It includes product design, component selection, material selection, and process planning. Mechanical manufacturing design achieves a better balance between all performance parameters and functionality while simultaneously reducing costs. In contrast, Computer Simulation Optimization refers to using computer-based tools and techniques to optimize production operations. It requires you to simulate the manufacturing process to find an optimal performance range. The model can improve the production efficiency, reduce the production cost, promote the production performance, and guarantee a better product quality in the intelligent manufacturing.

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